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# Adaptive Model-Based Mine Detection/Localization using Noisy Laser Doppler Vibration Measurements

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# Adaptive Model-Based Mine Detection/Localization using Noisy Laser Doppler Vibration Measurements

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***Abstract*—The acoustic detection of buried mines is hampered by the fact that at the frequencies required for obtaining useful penetration, the energy is quickly absorbed by the ground. A recent approach which avoids this problem, is to excite the ground with a high-level low frequency sound, which excites low frequency resonances in the mine. These resonances cause a low-level vibration on the surface which can be detected by a Laser Doppler Vibrometer. This paper presents a method of quickly and efficiently detecting these vibrations by sensing a change in the statistics of the signal when the mine is present. Results based on real data are shown.**

## I. Introduction

The detection of buried mines by acoustic means is hampered by the fact that, at frequencies high enough to render reasonable resolution of the mine that is suitable for detection purposes, the energy is rapidly absorbed in the ground [1]. An approach that is presently used is to excite the mine with a low-frequency, high-energy signal, which then excites a resonance in the mine [2]. The ensuing vibration causes a small but significant vibration on the surface of the ground, which can be detected by the use of a Laser Doppler Vibrometer (LDV). One drawback of the LDV approach is that it generates "speckle noise," a type of noise arising from the coherent nature of the laser beam [3]. The technique presented here utilizes an autoregressive model of this noise. This leads to an inverse filter that "whitens" the noise. Upon the appearance of any target data in the signal, a whiteness test indicates a detection. This approach has demonstrated improvement over the presently used bandpass filter approach. A potential further improvement is demonstrated by incorporating the prewhitener model in a Kalman filter. This has two advantages. First, it allows the introduction of a process noise term which provides an extra "tuning" parameter, and second, it provides the innovations sequence, which can be used as an identification tool, since its spectrum indicated the frequencies of the resonances.

## II. Laser Doppler Vibrometry

The Laser Doppler Vibrometer, or LDV, operates by scanning a laser beam over the surface of interest and comparing the scattered energy to a reference beam, thereby sensing the small vibratory movements of the relevant surface. Its performance is limited by the occurrence of speckle noise, which is a consequence of the coherent nature of the laser light [3]. If it is not dealt with in some way, it imposes a noise limit on the measurements.

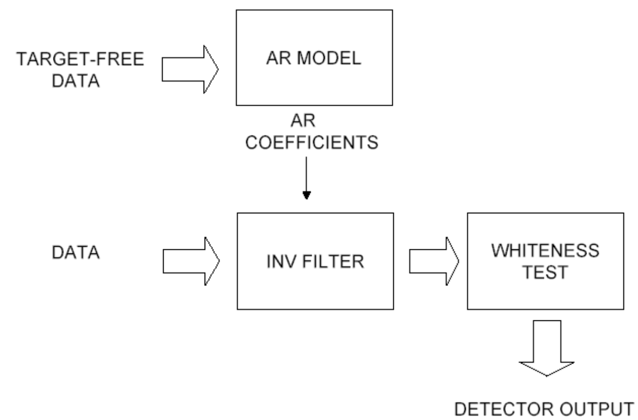


Fig. 1. Processing flow

The present approach is to scan a bandpass filter over the LDV output, seeking the highest output [2]. This can remove much of the speckle noise. This approach has shown some success, but is hampered not only by the remaining speckle noise, but by the fact that the resonance frequency is not known *a priori*. Also, since it is of interest to process the data as rapidly as possible, the time consumed by this scanning filter is problematical.

## III. Model-Based Detection

In the model-based approach we observe that there are two relevant physical phenomena that can be modeled; the noise and the target. Directing our attention first at the noise model, we note that the speckle noise is sufficiently stationary to permit an autoregressive (AR) model of the target-free time series to be used. This model allows an inverse filter to be constructed which when applied to the data, prewhitens it. A whiteness test [4] is then used to sense any deviation from whiteness, since the data containing the target is not well-represented by the AR model. This process is depicted in

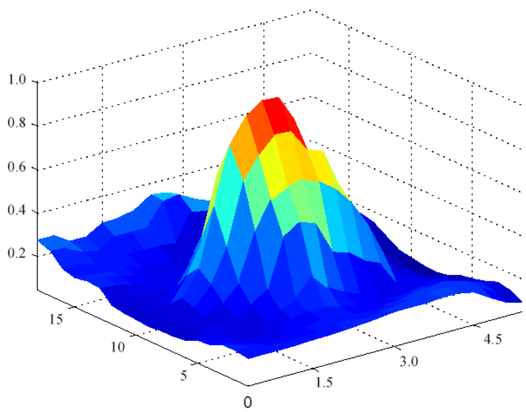


Fig. 2. Sliding filter results. The time axis runs from 0 to 6 seconds and the scan axis runs from 1 to 18.

Figure 1.

## IV. Data Properties

The test region had dimensions of $60 \times 60$ cm. The laser beam was swept across this region with $18$ scans, with a sweep speed of $10cm/sec$. Each is separated by about $5$ cm and the total time was $108$ seconds. The LDV was looking directly downwards ($90^o$).

The target is a VS $2.2$ anti-tank landmine (plastic mine) buried at $5$ cm meter depth in a sandy gravel road. The mine has been weathered in for many years. After FM-demodulation, the resulting sampling frequency is $976$ Hz. The signal used was a Maximum Length Sequence (MLS) of $1023$ points in one period. The loudspeakers were $2$ meters from the target, radiating sound signals between $100$ Hz and $250$ Hz at a very shallow grazing angle towards the road surface. The power on the ground surface was about $100$ dB (C) More detail on the experiment can be found in [2].

### A. Whitening Filter

The first block in Figure 1 depicts the AR model, which uses the Burg algorithm to provide the AR coefficients for the inverse filter. The second block, the inverse filter, is obtained by using the AR coefficients as the filter coefficients. This filter whitens the target-free data and the result is then passed to the whitening test. The whiteness test, which has the form of a log-likelihood test, acts as the detector, since the presence of the target data will cause the whiteness test to fail.

### B. Whiteness Test

The whiteness test we use here is the Weighted Sum Squared Residual or WSSR. It is given by

$$\rho(\ell) = \sum_{k=\ell-N+1}^{\ell} y(k) R_{yy}^{-1}(k) y(k); \quad \ell \geq N, \tag{1}$$

where $y$ is the data sequence and $R_{yy}$ is its covariance.

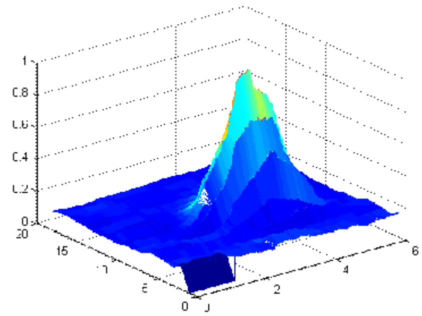

Fig. 3. Whiteness test results. The time axis runs from 0 to 6 seconds and the scan axis runs from 1 to 18.

## V. Kalman filter Approach

The Kalman filter transition matrix for this case is determined by the AR model and takes the following form.

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ a_N & a_{N-1} & a_{N-2} & \cdots & a_1 \end{bmatrix}. \tag{2}$$

Here, the $\{a_n\}$ are the AR coefficients. The state equation model (Gauss-Markov) takes the form

$$x(k|k) = Ax(k|k-1) + w(k-1) \tag{3}$$

and the measurement equation is given by

$$y(k) = Cx(k) + v(k), \tag{4}$$

with

$$C = [\, 0 \quad 0 \quad \cdots \quad 0 \quad 1 \,]. \tag{5}$$

In the above $w$ and $v$ are the Gaussian process noise and measurement noise, respectively, and $y$ is the measurement.

The linear Kalman algorithm [4] is carried out in the usual way, *viz.*

State prediction

$$\hat{x}(k) = A\hat{x}(k|k-1)$$

Compute measurement prediction

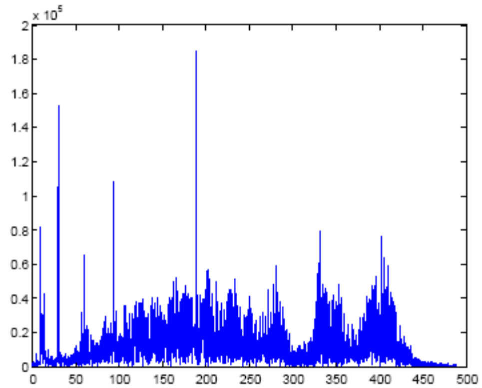


Fig. 4. Innovations sequence spectrum with no signal present

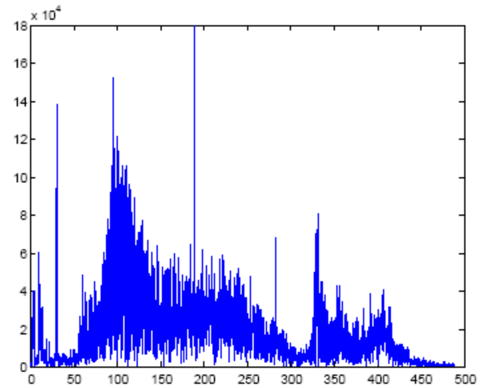


Fig. 5. Innovations sequence spectrum with signal present

$$\hat{y}(k|k-1) = C\hat{x}(k|k-1)$$

Compute innovations using new measurement $y(k)$

$$\epsilon(k) = y(k) - \hat{y}(k|k-1)$$

Compute Kalman gain

$$K(k) = \tilde{P}C^T R_{ee}^{-1}$$

Compute corrected state

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)\epsilon(k)$$

Here, $R_{ee}$ is the innovations covariance and $\tilde{P}$ is the state error covariance, both of which are computed recursively by the algorithm [4].

This approach is based on the following observation. If the AR coefficients provide a sufficiently faithful model of the signal free data, then the innovations sequence should be zero-mean and white. However, when target information is in the data, the model is no longer well-represented by the model, and consequently, the innovations sequence fails the whiteness test. The detection is then performed by applying the innovations sequence to the WSSR test in Equation 1.

As it turns out, the performance was no better that directly applying the prewhitened data to the WSSR. This is probably due to the fact that the SNR of the target data was so high. However, there is still interest in the Kalman approach here, since the spectrum of the innovations sequence provides a direct measurement of the resonance frequencies, thereby serving as an identification tool.

## VI. Results

The results using the prewhitener are shown in Figures 2 and 3. In Figure 2, the result using the sliding bandpass filter is shown. As can be seen, there is a strong detection showing a target approximately in the center of the test region. The result using the whiteness test is shown in Figure 4, where there is also a strong detection, but with a lower noise level. Note that the peak is shifted somewhat to a later time. This is a consequence of the fact that the whiteness test utilizes a sliding window.

Figures 4 and 5 show the innovations sequence spectra for the signal absent and signal present cases, respectively. As can be seen, there a strong mine resonance near $100$ Hz. The lower level resonance near $340$ Hz is a laser mirror resonance. Since this is not modeled by the Kalman filter, it is in both spectra.

## VII. Conclusion

It is seen that this approach provides a promising approach to buried mine detection. Normally, in such cases, one would hope to model the signal in order to provide improvement in performance, since the ability to model noise can sometimes be difficult. However in this case the particular character of speckle noise, especially its stationarity, permit such modeling. In the data shown here, the order of the AR model is $3$.

Although this approach outperformed the sliding filter method, another advantage of is that *a priori* knowledge of the signal spectrum is not necessary. Further, the resonances of the mine are accessible from the innovations spectrum, which permits a useful classification clue.

Even though the direct prewhitening method performed as well as the Kalman filter approach, it is felt that this is a consequence of the high SNR. In future work we hope to have access to data with a lower SNR.

## VIII. Acknowledgements

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